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PERFORMANCE OF ELECTRIC MINIBUSES WITH OPEN BOOTS

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Abstract: This study examines the influence of rear boot opening angles ($0^{\circ} - 90^{\circ}$) and vehicle speeds (60–140 km/h) on the aerodynamics, energy consumption, range, and maximum speed of an electric Toyota HiAce minibus. A framework combining Computational Fluid Dynamics (CFD) and longitudinal dynamics was utilized to develop a fourth–order nonlinear regression model for predicting the total drag coefficient. Statistical diagnostics confirmed the model’s reliability regarding residual normality and homoscedasticity. Results reveal that drag, energy consumption, and range exhibit a wavy variation pattern with boot opening. Aerodynamic drag becomes the dominant resistive force at high speeds, significantly increasing energy demand. The analysis identifies an optimal boot opening of approximately $10^{\circ} - 15^{\circ}$ that minimizes drag and maximizes range, outperforming the fully closed configuration. Although a secondary drag minimum occurs near 74° , it is discouraged due to vehicle stability and safety risks. Overall, the study highlights how minor geometric modifications significantly impact electric commercial vehicle performance and efficiency.

Keywords: Aerodynamic Drag, Boot Opening, Electric Minibus, Energy Consumption, Range

INTRODUCTION

Aerodynamic performance has long been recognized as a critical factor influencing vehicle energy consumption (Dinh, 2020; Eydgahi & Long, 2011; Kaleg et al., 2015), particularly for commercial and electric vehicles. The drag force acting on a moving vehicle increases with the square of velocity, making aerodynamic efficiency increasingly important at higher speeds (Jux et al., 2023; Malizia & Blocken, 2021). As a result, numerous studies have focused on understanding and reducing aerodynamic drag through both geometric optimization and flow control strategies (Gaylard et al., 2014; Good et al., 2011; Howell et al., 2014; Huminic & Huminic, 2017a; Mukut & Abedin, 2019; Quan, 2024; Schuetz, 2016; Urquhart et al., 2020; Xuan et al., 2025).

Commercial vehicles such as vans, minibuses, and trucks are typically characterized by bluff body geometries, which inherently produce large wake regions and high pressure drag. Recent CFD-based investigations confirm that flow separation and recirculation dominate the wake structure, significantly increasing drag and energy consumption (Xuan et al., 2025). These aerodynamic challenges are particularly relevant for box-shaped vehicles designed to maximize interior volume, where rear-end flow behavior strongly influences overall performance (Quan, 2024). Such findings emphasize the need for aerodynamic improvements specifically tailored to commercial vehicle geometries.

A substantial body of research has investigated the role of rear-end modifications in influencing

aerodynamic characteristics. The rear region of a vehicle is particularly important because it governs wake formation and pressure recovery. Recent studies using CFD and experimental approaches show that modifications such as spoilers and rear appendages significantly alter drag and lift behavior through changes in flow separation and wake structures (Badu et al., 2024; Öztemel et al., 2023). This sensitivity to rear geometry has also been demonstrated in modern parametric studies, where variations in rear aerodynamic devices and configurations lead to measurable differences in drag and vehicle stability (Fougere et al., 2024).

In addition to static body shapes, adjustable or add-on aerodynamic devices have been explored to improve performance. For example, studies on rear spoilers indicate that variations in angle of attack and profile significantly influence drag and downforce characteristics, often involving trade-offs between efficiency and stability (Badu et al., 2024; Öztemel et al., 2023). Similarly, passive flow control devices designed to delay flow separation have been shown to reduce drag and improve aerodynamic efficiency by modifying boundary layer behavior and wake dynamics (Bayındırlı & Çelik, 2024). These findings collectively demonstrate that even minor geometric adjustments can produce non-linear and sometimes counterintuitive aerodynamic effects.

Recent advancements in computational fluid dynamics (CFD) have enabled detailed parametric analyses of vehicle geometry. CFD-based studies allow researchers to systematically vary design parameters and evaluate their influence on drag

and flow behavior. For instance, recent work on vehicle body parameter optimization demonstrates that geometric variations significantly affect pressure distribution and drag coefficient, reinforcing the importance of design sensitivity analysis (Li et al., 2025). Additionally, high-fidelity simulations using realistic vehicle models such as DrivAer have highlighted the complex aerodynamic interactions between the vehicle body and rear aerodynamic devices, particularly in the wake region (Le et al., 2026).

Beyond aerodynamic performance alone, several studies have linked drag reduction directly to energy efficiency and fuel consumption. Reducing aerodynamic resistance remains a key strategy for lowering energy demand and improving vehicle efficiency, especially at higher speeds where drag becomes dominant (Li et al., 2025; Quan, 2024). This relationship is even more critical for electric vehicles, where energy consumption directly determines driving range. Consequently, optimizing aerodynamic performance is a key strategy for extending range and improving the viability of electric commercial transport.

Despite the extensive research on aerodynamic optimization and rear-end modifications, there remains a gap in the literature regarding the aerodynamic effects of operational configurations such as partially open rear doors or boots. While studies on spoilers, diffusers, and tailgate geometries provide valuable insights, they typically focus on fixed or design-stage modifications rather than variable configurations encountered during real-world use. In particular, the influence of rear boot opening angle on aerodynamic drag, energy consumption, and vehicle performance has not been comprehensively quantified.

Therefore, there is a need for systematic investigation into how such geometric variations affect aerodynamic behavior and vehicle efficiency. Integrating CFD analysis with vehicle dynamics modeling offers a promising approach to bridge this gap, enabling a more holistic understanding of the relationship between aerodynamic characteristics and performance metrics such as energy consumption and driving range.

MODEL DESCRIPTION

Geometric description of TOYOTA™ HiAce™ minibus

Since this study is an extension of a previous study (Oloruntoba & Okediji, 2021), hence the geometry details of the TOYOTA™ HiAce™ minibus are given as: the overall length of the minibus $L = 5.915$ m, the corresponding width $W = 1.950$ m and height $H = 1.990$ m. Pictorial representation of the vehicle geometry is given in Figure (1). Also based on the previous work, Figures (2) shows the TOYOTA™ HiAce™ minibus with simplified (Huminic

& Huminic, 2017b; Zhang et al., 2019) geometry with open boot.



Figure 2: Typical TOYOTA™ HiAce™ minibus with open boot
(Source: (Oloruntoba & Okediji, 2021)).

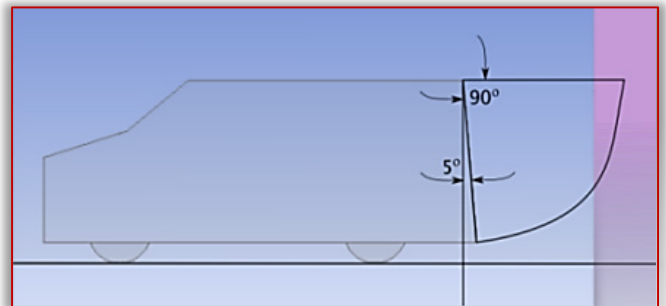


Figure 3: Simplified TOYOTA™ HiAce™ minibus with geometrical illustration of boot opening at $\theta = 5^\circ$ and $\theta = 90^\circ$; base geometry is at $\theta = 0^\circ$
(Source: (Oloruntoba & Okediji, 2021)).

Vehicle and Powertrain Modeling

The vehicle considered in this study is an electric-equivalent version of the Toyota HiAce 2020 minibus platform as mentioned previously (Oloruntoba & Okediji, 2021). The geometric characteristics and vehicle mass are based on manufacturer specifications for the HiAce minibus platform, while the electric powertrain parameters correspond to a typical electric drivetrain applicable to commercial minibus.

The primary vehicle parameters used in the analysis include vehicle mass m , frontal area A , aerodynamic drag coefficient C_d , rolling resistance coefficient C_{rr} , wheel radius r , and air density ρ . Powertrain parameters include motor torque T_m , motor maximum power $P_{motor,max}$, gear ratio G , gearbox efficiency η_g , drivetrain efficiency η_d , battery energy capacity $E_{battery}$, allowable depth of discharge DOD, and battery efficiency η_b .

The equivalent vehicle mass accounting for drivetrain rotational inertia is approximated as:

$m_{eq} = m + \frac{I_r}{r^2}$, where m_{eq} is the equivalent mass of the vehicle due to additional effect of rotational inertia of drivetrain components, I_r is the corresponding equivalent rotational inertia, and m represents mass of the vehicle. In practical vehicle simulations, this is often approximated as $m_{eq} \approx 1.05m$ for light commercial vehicles (Guzzella & Sciarretta, 2013)

Aerodynamic Coefficient Data Acquisition

The aerodynamic drag coefficient, C_d , is obtained through CFD simulations performed for different vehicle speeds and boot-opening angles. The simulation grid covers: Speeds (60, 80, 100, 120, 140 km/h) and Boot opening (0° , 5° , 10° , ..., 90°). The CFD results form a C_d surface, which is used both as reference data and to develop a regression model. Figure (4) presents the CFD data.

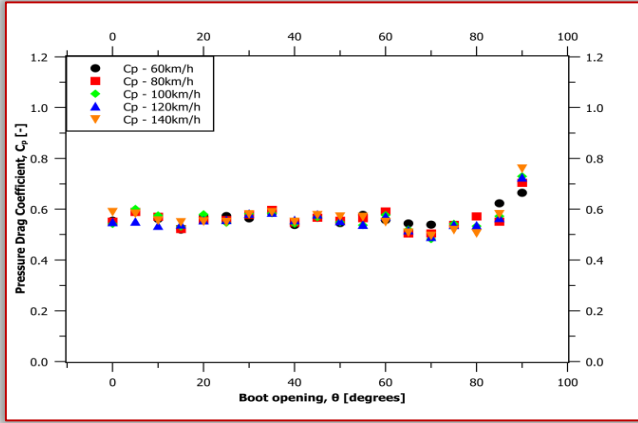


Figure 4: CFD data of total drag coefficient of minibus at various vehicle speeds as a function of boot opening.

Nondimensionalization

A nondimensional approach is applied in order to generalize the results and reduce numerical sensitivity. Equation (1) provides the nondimensional terms for vehicle speed, boot opening, and aerodynamic drag coefficient.

$$u = \frac{v}{V_{ref}}, \theta^* = \frac{\theta}{\theta_{ref}}, C_{d*} = \frac{C_d}{C_{d,ref}} \quad (1)$$

where V_{ref} and θ_{ref} are the maximum speed and boot-opening angle in the CFD dataset, respectively. The reference drag coefficient, $C_{d,ref}$, is taken as the mean of all C_d values. This nondimensionalization is applied consistently in: Regression model fitting, Drag and rolling power calculations, and Maximum speed estimation. This approach allows the results to be generalised to other vehicles of similar geometry and scales.

Regression Modeling of Drag Coefficient

A fourth-order polynomial regression model is developed to predict C_d as a function of nondimensional speed u and boot-opening angle θ^* , $C_d(u, \theta^*)$, as shown in Equation (2); the corresponding coefficients of the regression model are given in Table 1, with $R^2 = 0.7294$. Scatter plot comparison between CFD data and the regression model is given in Figure (5), with maximum and minimum absolute percentage error values of 7.074 and -7.611 respectively.

$$C_d(u, \theta^*) = \beta_0 + \beta_1 u + \beta_2 u^2 + \beta_3 u^3 + \beta_4 u^4 + \beta_5 \theta^* + \beta_6 (\theta^*)^2 + \beta_7 (\theta^*)^3 + \beta_8 (\theta^*)^4 + \beta_9 u \theta^* + \beta_{10} u^2 \theta^* + \beta_{11} u (\theta^*)^2 \quad (2)$$

Table 1: Coefficients for the nonlinear regression $C_d(u, \theta^*)$ model.

S/N	Coefficients of Equation (2)	Value
1	β_0	0.90886840277163849500
2	β_1	-2.08825479973860561600
3	β_2	4.89110370184090470502
4	β_3	-4.92590284234878428293
5	β_4	1.81168974056257892080
6	β_5	-0.52859336145647428662
7	β_6	3.71653356037676729784
8	β_7	-7.16047303429947756825
9	β_8	4.12549386585355915003
10	β_9	-0.15554878904377458793
11	β_{10}	0.02662575576316500089
12	β_{11}	0.09293850067428972850

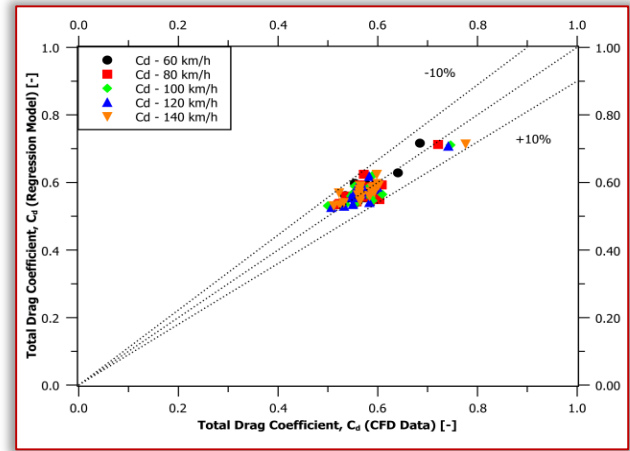


Figure 5: Comparison of total CFD and regression prediction of drag coefficient.

Model Validation and Diagnostic Justification

The reliability of the nonlinear regression model for $C_d(u, \theta^*)$ is supported by several key diagnostic plots that assess the behaviour of the residuals:

— **Assumption of Normality:** The Histogram of Residuals (Figure (6)) shows a distribution of errors that is roughly bell-shaped and centered around zero, indicating that the model's prediction errors are normally distributed. This is further corroborated by the Normal Q-Q plot (Figure (7)), where the data points closely follow the theoretical diagonal line, confirming that the residuals do not significantly deviate from a normal distribution.

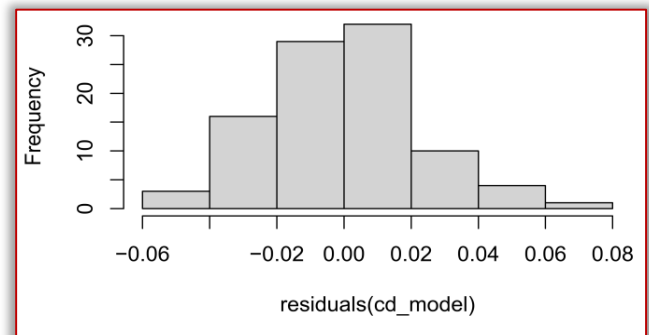


Figure 6: Histogram of Residuals for $C_d(u, \theta^*)$ nonlinear regression model.

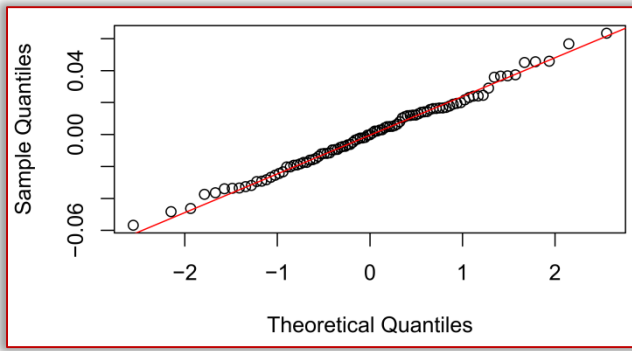


Figure 7: Normal Q–Q plot for $C_d(u, \theta^*)$ nonlinear regression model.

- **Linearity and Independence:** The Residual vs. Fitted plot (Figure (8)) demonstrates that the residuals are scattered randomly around the horizontal zero line without any distinct curved patterns. This indicates that the nonlinear model effectively captures the relationship between the independent variables (speed u and boot angle θ^*) and $C_d(u, \theta^*)$, and that the relationship is appropriately specified.

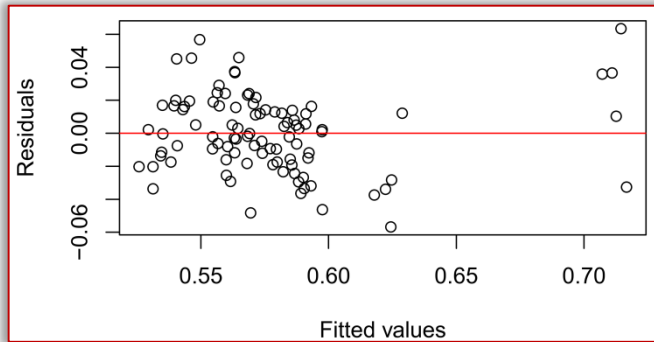


Figure 8: Residual vs. Fitted plot for $C_d(u, \theta^*)$ nonlinear regression model.

- **Homoscedasticity (Constant Variance):** The Scale-Location (Spread-Location) plot (Figure (9)) shows that the square root of the standardized residuals is spread relatively evenly across the range of fitted values. The lack of a clear "fan" or "funnel" shape suggests that the variance of the error terms is constant (homoscedastic), ensuring that the model's predictive accuracy remains consistent across different speeds and opening angles.

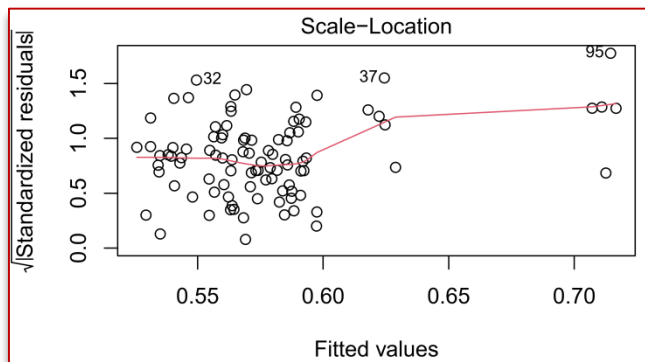


Figure 9: Scale–Location (Spread–Location) plot for $C_d(u, \theta^*)$ nonlinear regression model.

- **Influence and Outlier Detection:** The Residuals vs. Leverage plot (Figure (10)) is used to identify

any influential observations that might disproportionately affect the regression coefficients. While specific data points such as 95, 19, and 57 are highlighted, they do not exceed the critical Cook's distance thresholds (typically 0.5 or 1), suggesting that no single observation is skewing the model's results.

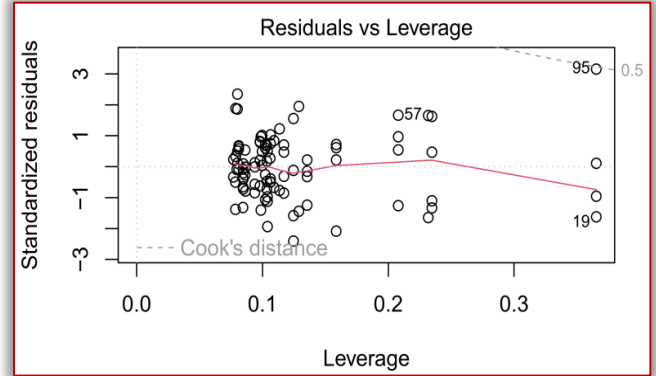


Figure 10: Residuals vs. Leverage plot for $C_d(u, \theta^*)$ nonlinear regression model.

By satisfying these statistical criteria, the nonlinear regression model is validated as a robust tool for calculating C_d . This ensures that the subsequent calculations for aerodynamic drag force, energy consumption E_{km} , and vehicle range are based on a statistically sound and high-fidelity representation of the vehicle's aerodynamic behavior.

Longitudinal Vehicle Dynamics Model

Vehicle motion is modeled using the standard longitudinal dynamics equation (Equation (3)), which balances the tractive force generated at the wheels with the resistive forces acting on the vehicle (Chan, 2007; Ehsani et al., 2018), where F_{trac} is tractive force generated at wheels, F_{rr} represents rolling resistance, F_{aero} stands for aerodynamic drag, and F_{grade} is road grade resistance. a is the vehicle acceleration.

$$F_{trac} = F_{rr} + F_{aero} + F_{grade} \quad (3)$$

Rolling resistance is calculated as shown in Equation (4), where C_{rr} is the rolling resistance coefficient, and g is the acceleration due to gravity. Aerodynamic drag force is calculated using Equation (5). The symbols ρ represents density of air, A stands for cross-sectional area of the vehicle, C_d is the total coefficient of drag of the vehicle, and v represents vehicle velocity. Aerodynamic drag plays a dominant role in vehicle energy consumption at medium to high speeds (Hucho, 2013).

$$F_{rr} = mgC_{rr} \quad (4)$$

$$F_{aero} = \frac{1}{2} \rho A C_d v^2 \quad (5)$$

The effect of road inclination or slope θ is also important. Grade Resistance, which largely

influenced by θ is determined using Equation (6). This term becomes significant in hill climbing or heavy-load transport scenarios.

$$F_{\text{grade}} = mg \sin \theta \quad (6)$$

The tractive force at the wheels is derived from the motor torque transmitted through the drivetrain (Equation (7)), where T_{ω} is the wheel torque, G represents gear ratio, and η_g is gearbox efficiency. The tractive force is therefore: determined in Equation (8), where r is the wheel radius. This approach is commonly used in EV drivetrain modeling (Ehsani et al., 2018).

$$T_{\omega} = T_m G \eta_g \quad (7)$$

$$F_{\text{trac}} = \frac{T_{\omega}}{r} \quad (8)$$

Maximum Vehicle Acceleration

The instantaneous vehicle acceleration $a(v)$ is obtained from Newton's second law as shown in Equation (9), where the total resistive force F_{res} is the summation of F_{rr} , F_{aero} and F_{grade} . Maximum acceleration occurs at low vehicle speed when the electric motor operates in the constant-torque region (Chan, 2007).

$$a(v) = \frac{F_{\text{trac}}(v) - F_{\text{res}}(v)}{m_{\text{eq}}} \quad (9)$$

Maximum Speed Determination

The maximum vehicle speed occurs when the available power from the motor equals the power required to overcome resistive forces. The electrical power drawn from the battery defined as $P_{\text{battery}} = V_{\text{max}} I_{\text{max}}$. The minimum of $P_{\text{motor,max}}$ and P_{battery} is required to determine maximum speed as shown in Equation (10). This nonlinear equation is solved numerically.

$$P_{\text{available}} = \frac{(F_{\text{rr}} + F_{\text{aero}} + F_{\text{grade}})v_{\text{max}}}{\eta_d} \quad (2)$$

Energy Consumption and Range Estimation

The energy consumption per unit distance E_{km} is computed from the resistive forces acting on the vehicle as shown in Equation (11). The usable battery energy is determined as $E_{\text{usable}} = E_{\text{battery}} \cdot \text{DOD} \cdot \eta_b$. Thereafter, the theoretical vehicle range is estimated as shown in Equation (12) (Fiori et al., 2016).

$$E_{\text{km}} = \frac{F_{\text{res}}}{\eta_d} \quad (11)$$

$$\text{Range} = \frac{E_{\text{usable}}}{E_{\text{km}}} \quad (12)$$

RESULTS AND DISCUSSION

The analysis of the electric-equivalent Toyota HiAce minibus reveals that the wavy variation pattern observed in aerodynamic drag coefficients directly dictates the vehicle's energy consumption and operational range. These results, derived from a combination of CFD data and longitudinal dynamics modeling, are detailed below.

Energy Consumption

The plot of energy consumption per unit distance E_{km} , shown in Figure (11), follows a non-linear, wavy pattern as a function of the boot opening angle θ , mirror-imaging the behavior of the total drag coefficient C_d .

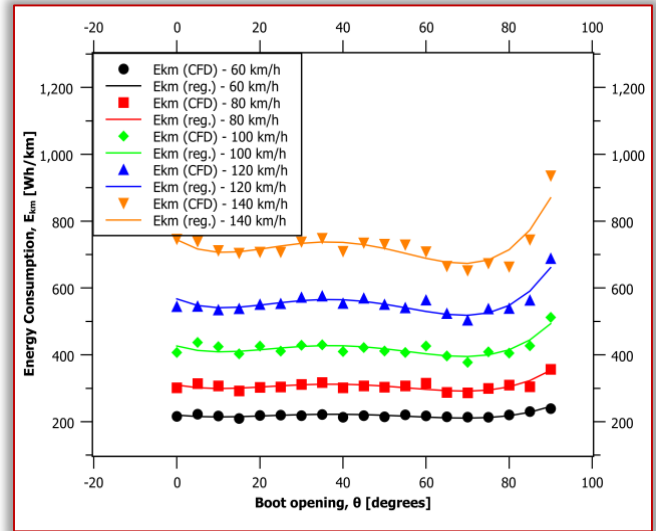


Figure 11: Energy consumption of minibus at various vehicle speeds as a function of boot opening.

- **Impact of Speed:** As shown in Figure (11), energy consumption increases significantly with vehicle speed. At lower speeds, such as 60 km/h, E_{km} remains relatively stable despite changes in boot opening; however, at 140 km/h, the wavy fluctuations become highly pronounced. At these high speeds, aerodynamic drag becomes the dominant resistive force, causing E_{km} to peak alongside total drag coefficient C_d at boot opening $\theta = 41.84^\circ, 41.84^\circ$ and 41.84° .
- **Prediction Accuracy:** Figure (12) illustrates the error margins for the regression model used to predict energy consumption E_{km} . The results indicate that while the model is highly accurate for small boot openings, the absolute percentage error can reach up to 7.611% at $\theta = 90^\circ$. This higher error rate is attributed to highly turbulent flow conditions that are more difficult to capture with steady-state regression models.

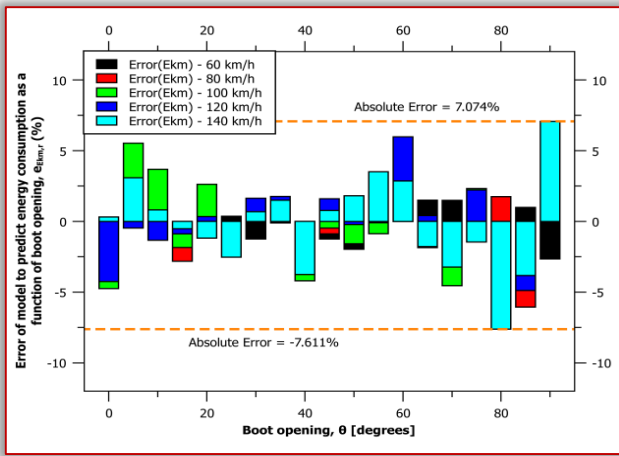


Figure 12: Error of model to predict energy consumption of minibus at various vehicle speeds as a function of boot opening.

Driving Range

The theoretical driving range of the minibus is inversely proportional to its energy consumption (Equation (13)). The range of the minibus as a function of speed and boot opening are presented and discussed:

— **Range Variation:** Figure (13) demonstrates that the maximum range is achieved at vehicle speeds where resistive forces are minimised. Similar to energy consumption, the range exhibits a wavy pattern across different boot opening angles. The highest range is consistently observed at the lower vehicle speeds (60 km/h) and at the optimal boot opening (i.e. where drag is minimized) of $\theta = 15^\circ$ and $\theta = 10^\circ$ for CFD data and regression model prediction respectively; a similar occurrence was observed at $\theta = 9.30^\circ$ for fossil powered minibus (Oloruntoba & Okediji, 2021). The send occurrence of highest range (i.e. $\theta = 75^\circ$ and $\theta = 70^\circ$ for CFD data and regression model prediction respectively) is not recommend for safety reasons (Oloruntoba & Okediji, 2021).

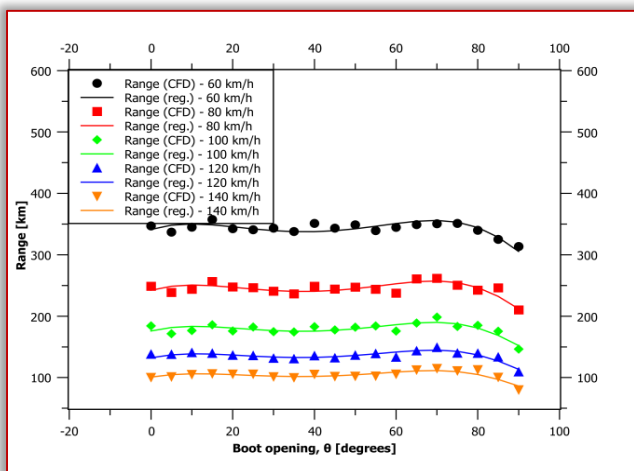


Figure 13: Range of minibus at various vehicle speeds as a function of boot opening.

— **Speed Sensitivity:** Increasing the speed from 60 km/h to 140 km/h results in a drastic reduction

in range, as the energy required to overcome aerodynamic resistance grows cubically with velocity.

— **Model Reliability:** According to Figure (14), the regression model for range prediction shows an absolute percentage error peak of 7.612% at . This discrepancy mirrors the errors found in the prediction of energy consumption.

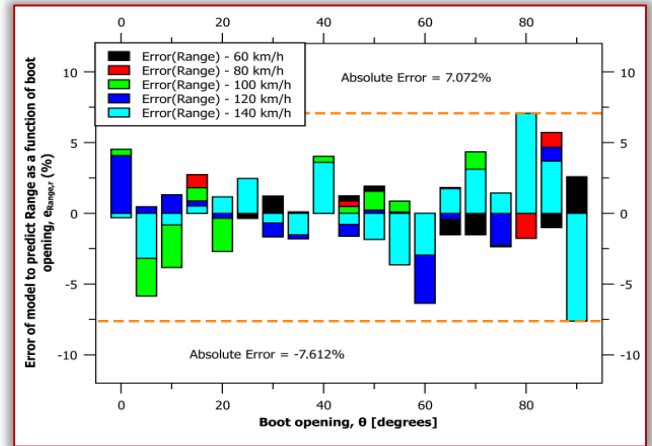


Figure 14: Error of model to predict range of minibus at various vehicle speeds as a function of boot opening.

Effect of Boot Opening on Maximum Speed

The results in Figure (15) confirm that the "base geometry" ($\theta = 0^\circ$) is not necessarily the most efficient configuration for an electric minibus. The optimum boot opening remains $\theta = 15^\circ - 20^\circ$ and $\theta = 10^\circ - 15^\circ$ for CFD data and regression model prediction respectively, which provides a lower C_d (0.561) compared to the closed boot (0.5895), thereby maximizing the vehicle's maximum speed at 145.44 km/h.

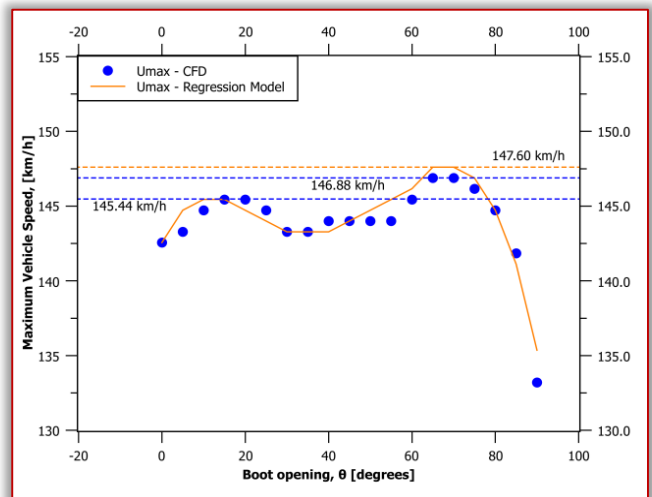


Figure 15: Error of model to predict range of minibus at various vehicle speeds as a function of boot opening.

Furthermore, while a second minimum drag point exists at $\theta = 65^\circ - 70^\circ$ for both CFD data, with $v_{\max} = 146.88$ km/h, and regression model prediction, with ($v_{\max} = 147.60$ km/h), it is not recommended for EV operation. From a practical standpoint, such wide openings significantly shift the vehicle's center of gravity, negatively

impacting handling and safety. For commercial electric transporters, maintaining the boot at the optimal angle offers the best balance between additional cargo capacity, energy efficiency and maximum speed.

CONCLUSIONS

This study investigated the influence of rear boot opening angle on the aerodynamic performance, energy consumption, and operational range of an electric-equivalent Toyota HiAce minibus. Using CFD-generated aerodynamic data combined with longitudinal vehicle dynamics modeling, a nonlinear regression model was developed to represent the drag coefficient as a function of vehicle speed and boot opening angle. The regression model demonstrated acceptable predictive capability with ($R^2 = 0.7294$) and maximum absolute percentage errors of approximately $\pm 7.6\%$, while diagnostic tests confirmed that the residuals satisfied normality, independence, and homoscedasticity assumptions.

The results show that aerodynamic drag strongly governs the vehicle's energy consumption and range, particularly at higher speeds where drag becomes the dominant resistive force. Consequently, both energy consumption and driving range exhibit a wavy variation pattern that closely follows the behaviour of the drag coefficient across different boot opening angles. As vehicle speed increases from 60 km/h to 140 km/h, the sensitivity of energy consumption to aerodynamic variations becomes significantly more pronounced, leading to substantial reductions in driving range.

Importantly, the analysis demonstrates that the base configuration with a fully closed boot ($\theta = 0^\circ$) does not provide the most aerodynamically efficient condition. Instead, a small boot opening of approximately $\theta = 10^\circ - 15^\circ$ produces the lowest drag coefficient $C_d = 0.561$, resulting in reduced energy consumption and improved driving range. Although a secondary drag minimum appears at large opening angles (approximately $\theta = 65^\circ - 70^\circ$), such configurations are not recommended due to safety concerns, including potential shifts in vehicle stability and center of gravity. Similarly, the maximum vehicle speed is achieved within a moderate boot opening range of approximately $\theta = 10^\circ - 15^\circ$, confirming that slight geometric modifications can influence overall vehicle performance.

Overall, the findings highlight the importance of aerodynamic optimization in electric commercial vehicles. Even minor geometric changes, such as partial rear-door opening, can produce measurable improvements in vehicle efficiency and range. The developed regression-based aerodynamic model provides a practical tool for integrating aerodynamic effects into vehicle performance

simulations without the need for repeated CFD analysis.

Future work may extend this research by incorporating transient aerodynamic simulations, experimental wind-tunnel validation, and real-world driving cycles to further refine the predictive accuracy of the model and evaluate additional geometric modifications for improving the energy efficiency of electric minibuses.

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